

QuadAI at SemEval-2026 Task 3: Ensemble Learning of Hybrid RoBERTa and LLMs for Dimensional Aspect-Based Sentiment Analysis

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Abstract

We present our system for SemEval-2026 Task 3 on dimensional aspect-based sentiment regression. Our approach combines a hybrid RoBERTa encoder, which jointly predicts sentiment using regression and discretized classification heads, with large language models (LLMs) via prediction-level ensemble learning. The hybrid encoder improves prediction stability by combining continuous and discretized sentiment representations. We further explore in-context learning with LLMs and ridge-regression stacking to combine encoder and LLM predictions. Experimental results on the development set show that ensemble learning significantly improves performance over individual models, achieving substantial reductions in RMSE and improvements in correlation scores. Our findings demonstrate the complementary strengths of encoder-based and LLM-based approaches for dimensional sentiment analysis. Our development code and resources will be shared at <https://github.com/aaronlifenghan/ABSentiment>

1 Introduction

Aspect-based sentiment analysis (ABSA) is a natural language processing (NLP) task that involves a few sub-tasks that include aspect term extraction, aspect category detection, opinion extraction, and aspect sentiment classification (Zhang et al., 2022). It has witnessed the traditional ML, deep learning, and pretrained language model (PLM) approaches. The Transformer-based models (both encoders (Liao et al., 2021; Chauhan et al., 2025) and decoders (Mughal et al., 2024; Ventirozos et al., 2025b,a)) have been the dominant methods nowadays for such tasks, while challenges remain, such as data scarcity, domain application, and modeling complex aspect-opinion relationships (Nazir et al., 2020; Zhang et al., 2022).

The shared task we attended this year has two tracks: Track-A “Dimensional Aspect-Based Senti-

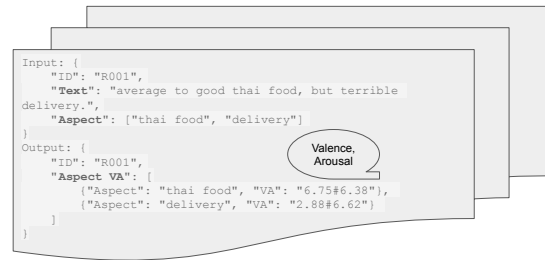


Figure 1: Example of TaskA1 data: Dimensional Aspect Sentiment Regression (DimASR)

ment Analysis (DimABSA)” and Track-B “Dimensional Stance Analysis (DimStance)”. We attended Task-A.1 “DimASR - Valence-Arousal (VA) Prediction” and Track-B, leaving “A.2: DimASTE - Triplet Extraction” and “A.3: DimASQP - Quadruplet Extraction” into our future work. The shared task data is described at (Lee et al., 2026; Becker et al., 2026) As examples of Task-A1 and Task-B, we list the text format of input and output in Figure 1 and 2. Valence indicates positivity and negativity with more dimensions. Arousal indicates emotional intensity from high to low. For instance, (Happy, Delight, Excited) can be located in the corner of “positive and high” emotion, while (depressed, bored, tired) can be in the “negative and low” emotion (Yu et al., 2026).¹

In this work, we introduce related work to our proposed method, the methodology design and development (Hybrid RoBERTa, LLMs, ensemble), the evaluation results from development sets, and our submissions to the shared task. Due to unforeseen circumstances, we did not manage to submit all the methods we developed; however, we will continue our testing for offline development, and our codes and resources will be shared publicly for open science.

¹<https://github.com/DimABSA/DimABSA2026>

<p>Input: {"ID": "stance26_aspect_va_dev_10",</p> <p>"Text": "Say somehow we succeed and now have access to unlimited clean energy. What happens then ? Do we swap over to this new energy ? Do politicians in the pocket of oil and gas companies stop it from progressing ? Does having no energy limits lead to an even greater population problem around the world ? Could it lead to space exploration with rockets that have unlimited fuel ? I'm far too dumb to understand the science but it is crazy to me that it is something I could potentially see in my lifetime.",</p> <p>"Aspect": ["unlimited clean energy", "space exploration"] }</p>
<p>Output: {"ID": "stance26_aspect_va_dev_10",</p> <p>"Aspect_VA": [{"Aspect": "unlimited clean energy", "VA": "7.33#6.83"},</p> <p>{"Aspect": "space exploration", "VA": "6.50#6.00"}]}</p>

Figure 2: Example of TaskB data: Dimensional Aspect Sentiment Regression (DimASR)

2 Related Work

2.1 Beyond VA Scores

In addition to the Valance and Arousal (VA) score, Shi et al. (2025) tried to use another psychological emotion dimension ‘‘Dominance’’, i.e., the degree of control or influence. To address the issues of standard ABSA models that rely on word embeddings and attention but do not use structured emotion knowledge, they proposed the Graph Attention Network (GAT) method to model relationships between words and capture the syntactic dependencies. Similarly, there are other recent works using graph knowledge to address sentiment analysis, such as ReviewGraph (de Vink et al., 2025).

2.2 Language/Domain Specific ABSA

For language-specific ABSA, Lee et al. (2024) introduced a shared task for the Chinese language, which attracted 11 teams, focusing on intensity prediction, triplet extraction and quadruple extraction.

For domain specific work on ABSA, Chakraborty et al. (2020) used active learning on scientific reviews, using 8,000 peer reviews from ICLR conference, including (review text, score, paper decision). The work focused on the relationship between aspect sentiment (positive/negative) and paper outcome (accept/reject).

2.3 Hybrid Models for ABSA

Zhang et al. (2024) used hybrid setting of BERT based encoder models and LLMs. They first use BERT pipeline to extract aspects, categories, and opinions, then use LLM with QLoRA fine-tuning

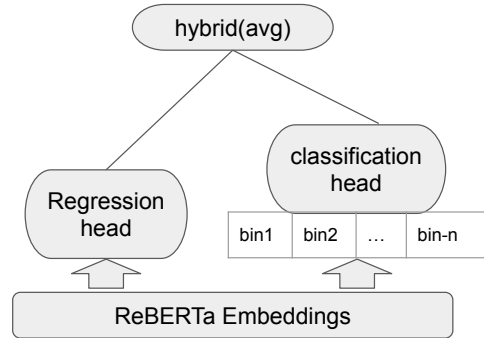


Figure 3: Hybrid RoBERTa

to predict sentiment intensity based on the BERT outputs.

Another hybrid model conducted by Liang et al. (2022) combines neural networks and contextual feature representations. Their model integrates word embeddings with attention mechanisms to capture aspect-specific contextual information. Experimental results demonstrated that the hybrid approach outperforms traditional neural models on benchmark datasets. This work highlights the effectiveness of hybrid architectures for fine-grained sentiment prediction.

More challenges, tasks, and methodologies on ABSA can be found in earlier surveys (Nazir et al., 2020; Zhang et al., 2022).

3 Methodology

3.1 Hybrid RoBERTa

We designed a hybrid encoder-based model using averaged scores from regression and discretized bin integrated classification, as shown in Figure 3. We firstly used RoBERTa embedding as the encoder. Then, in parallel, we trained a regression head and a discretized classification head. The core idea of discretizing the target space is that we take the continuous embedding variable and split it into n bins. The final layer outputs an n -dimensional logit vector then applied with softmax and trained with cross-entropy loss. The advantage of discretized classification is that it is expected to be a more stable training than regression and expresses confidence over bins.

Lastly, the final prediction of Hybrid RoBERTa is obtained by averaging both outputs ($w = 0.5$). We list the equations below. Regression output:

$$\hat{y}_{reg} \quad (1)$$

Classification expected value:

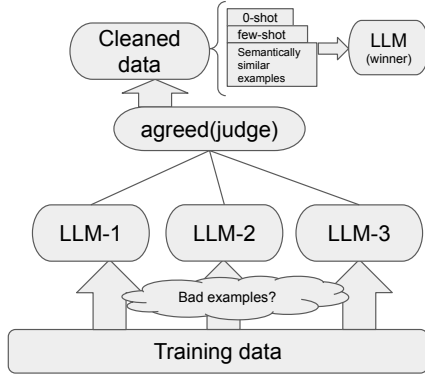


Figure 4: Triple-LLMs workflow

$$\hat{y}_{cls} = \sum_{i=1}^B p_i c_i \quad (2)$$

Final prediction:

$$\hat{y} = w\hat{y}_{reg} + (1 - w)\hat{y}_{cls} \quad (3)$$

Training objective:

$$L = L_{reg} + \alpha L_{cls} \quad (4)$$

3.2 LLMs

As a starting point, we explore the difference between:

- zero-shot prompting (no examples)
- random examples (40, 60)
- semantically picking similar examples (40, 60, 100, 200, 600)

The semantical similarity is according to the embedding similarity scores at sentence level. We utilized the OpenAI’s model for sentence embeddings².

Looking into some examples, we also decided to filter out low quality ones, such as cases where the labels do not look right. We call this step as Data Cleaning. The step involved firstly using HDB-Scan³ to cluster all the ones used for in-context learning (i.e. training-set) instances according to the two dimensions of valence and arousal. HDB-Scan uses the DBScan approach but converts it into hierarchical clustering, for which we used the given, default, hyper-parameters for the clustering.

²text-embedding-3-large

³<https://github.com/scikit-learn-contrib/hdbscan>

```

S - -
- you are an expert in sentiment analysis.
Below is a cluster of aspect-sentiment examples grouped by
similar
valence-Arousal A values.

D S:
- valence: 0.5 negative to 0.5 positive
- Arousal: 0.5 calm to 0.5 intense

S A S:
examples_text

AS : dentif which examples if an have
spurious/incorrect A labels
that don't match the text sentiment. An example is spurious
if:
. the A values don't match the sentiment expressed in the
text
2. the aspect sentiment is clearly different from the labeled
values
. the label seems inconsistent with similar examples in this
cluster

return valid S with the text:

spurious_indices : 0 2
reasoning : example 0: text is 0.5 negative but valence
is too high.
example : ...

if no examples are spurious return:
spurious_indices : reasoning : All labels appear
correct

```

Figure 5: Cluster critique prompt for VA-based sentiment analysis

Following for each cluster we had separate three LLMs be presented each cluster, similar VA scores, and ask in the prompt to pinpoint which one of these is an outlier or not. The data cleaning prompt includes: Persona, Metric Definitions, Cluster examples, and Returns, which are detailed in Figure 5.

Finally, if all three LLMs agree that a specific instance(s) in a cluster is at outlier, we would remove them from the available pool of in-context learning candidates.

This is shown in Figure 4. Exact LLMs we used for this task are “gemini”, “claude”, and “gpt5.2” for data cleaning with cross validation, and “gemini” for last stage prompting as the best performing LLM.

To reduce variance and improve model robustness, we explore the ensemble learning strategy, which will be described below.

3.3 Ensemble Learning

For Ensemble Learning, we design the prediction-level fusion (*aka* late fusion or model stacking) of Hybrid RoBERTa and LLMs with optional other features, as in Figure 6. For this work, we incorporate lexical sentiment features derived from VADER (Hutto and Gilbert, 2014), including compound, positive, negative, and neutral polarity

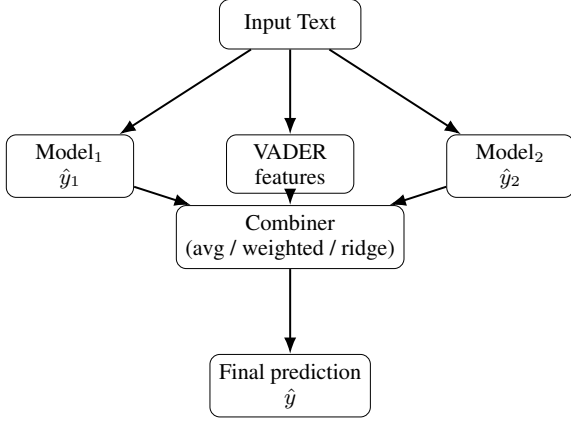


Figure 6: Prediction-level ensemble architecture combining base models and optional VADER features.

scores, as auxiliary inputs to the ensemble combiner.

We detail the ensemble prediction into mathematical formulas below: Given K base models, each producing a prediction \hat{y}_k for an input x , the final prediction is obtained via a combiner $g(\cdot)$:

$$\hat{y} = g(\hat{y}_1, \hat{y}_2, \dots, \hat{y}_K, \mathbf{f}), \quad (5)$$

where \mathbf{f} denotes optional external features (e.g., VADER scores).

Simple averaging:

$$\hat{y} = \frac{1}{K} \sum_{k=1}^K \hat{y}_k \quad (6)$$

Weighted averaging:

$$\hat{y} = \sum_{k=1}^K w_k \hat{y}_k, \quad \sum_{k=1}^K w_k = 1 \quad (7)$$

Ridge stacking:

$$\hat{y} = \mathbf{w}^\top [\hat{y}_1, \hat{y}_2, \dots, \hat{y}_K, \mathbf{f}] + b \quad (8)$$

The VADER features include: compound (continuous $[-1, 1]$), pos, neu, neg. So the stacking vector becomes:

$$\mathbf{x} = [\hat{y}_1, \hat{y}_2, \text{compound}, \text{pos}, \text{neu}, \text{neg}]$$

The rationale for including VADER as a feature is that the ensemble combines a lexicon and rule-based component, which is domain-robust and fast, with neural-based encoder models and LLMs.

Training objective (ridge stacking). Given training targets $\mathbf{y} \in \mathbb{R}^n$ and the design matrix $\mathbf{X} \in \mathbb{R}^{n \times (K+F)}$ whose i -th row is $\mathbf{x}^{(i)} = [\hat{y}_1^{(i)}, \dots, \hat{y}_K^{(i)}, \mathbf{f}^{(i)}]$, we learn \mathbf{w} and b by:

$$\min_{\mathbf{w}, b} \frac{1}{n} \|\mathbf{y} - (\mathbf{X}\mathbf{w} + b\mathbf{1})\|_2^2 + \lambda \|\mathbf{w}\|_2^2, \quad (9)$$

We construct \mathbf{X} using out-of-fold predictions of the base models to avoid label leakage.

4 Model Training and Development

4.1 Hybrid ReBERTa for Track-A1

The system performance on the development set of *laptop* category from encoder-based models is shown in Table 1 and 2. Table 1 presents the overall comparisons among regression-only, discretization-bin, and hybrid (averaging two). From the Error score metrics, we can see that the Hybrid model produced much better output on two metrics, MSE and RMSE, which have a bigger margin decrease in the error scores. However, it produced similar (or comparable) scores on RMSE(v) and RMSE(a), to regression-only and Bin models, respectively. For Pearson correlation scores, the Regression-only model produced the highest scores, though not much difference from the Hybrid model. Table 2 displays the Top-10 hybrid configurations ranked by averaging RMSE on the Laptop Dev set. We tried different sets of triple values for the parameters exhaustively; however, for future development, it would be more suitable to carry out automated hyperparameter tuning, e.g., OPTUNA (Akiba et al., 2019) to explore.

In addition, Table 3 shows the Hybrid RoBERTa performance on Task-A1 *restaurant* dev data. We can see from the scores that the hybrid model achieved the best performance on this data across all tested metrics, including both error scores and correlations. Importantly, the MSE score of the hybrid model is almost down to half that of the regression model (0.4919 vs 0.8176). Large improvement margins can also be observed from RMSE scores.

4.2 LLMs on Track-A Laptop Dev

The LLM output evaluation on the *laptop* Dev set is shown in Table 6, where we can see that, in comparison to Hybrid RoBERTa in Table 2, the LLMs produced an even lower RMSE score of 0.695, vs 0.7361. In addition, it increased the correlation mean score from 0.7231 to 0.757.

4.3 Ensemble on TrackA Laptop Dev

Table 4 shows the results from ensemble learning of two models, with/without the VADER feature on

Table 1: Performance of the Hybrid RoBERTa model on SemEval Task 1 (**Laptop**, Dev set). The model combines a regression head and a discretized classification head (31 bins), with the final prediction obtained by averaging both outputs ($w = 0.5$). Error categories: lower is better; in 3 categories hybrid is much better, except for RMSE that is comparable to Bin. Pearson correlation ρ higher is better rho(Regress>Hybrid>Bin)

Model Variant	MSE ↓	RMSE ↓	RMSE _v ↓	RMSE _a ↓	ρ_v ↑	ρ_a ↑	ρ_{mean} ↑
Regression only	0.6140	0.7836	0.7201	0.8423	0.9102	0.5505	0.7304
Bin (expected value)	0.6238	0.7898	0.8340	0.7430	0.8974	0.5126	0.7050
Hybrid (average)	0.5419	0.7361	0.7214	0.7506	0.9074	0.5388	0.7231

Table 2: Top-10 Hybrid configurations ranked by average RMSE on the **Laptop** Dev set. *num_bins* denotes the number of discretization bins, α the classification loss weight, and w the regression–classification averaging weight.

<i>num_bins</i>	α	w	RMSE _{avg} ↓	ρ_{mean} ↑	ρ_a ↑
31	0.5	0.5	0.7361	0.7231	0.5388
11	1.0	0.5	0.7368	0.7182	0.5277
31	0.5	0.4	0.7376	0.7252	0.5421
7	0.2	0.5	0.7405	0.7287	0.5473
31	0.5	0.3	0.7431	0.7270	0.5448
11	1.0	0.4	0.7448	0.7185	0.5278
7	0.2	0.4	0.7473	0.7293	0.5485
11	0.5	0.5	0.7481	0.7251	0.5523
31	1.0	0.5	0.7488	0.7138	0.5278
31	0.2	0.4	0.7516	0.7151	0.5234

the *laptop* data, which show much improvement in comparison to individual models (hybrid RoBERTa and LLMs), especially on RMSE scores. For the weighted ensemble, weights were selected via grid search over the interval $[0, 1]$ with step size 0.1, optimizing RMSE on the development set. The goal is that 1) better models get more influence; 2) it reduces bias compared to equal averaging. The experimental results show that average weighting produced RMSE score 0.6399 vs Weighted 0.6344 (lower and better). The results also show that the VADER feature did not make an improvement in the evaluation scores, even a slight degradation, which indicates that VADER probably adds noise or a redundant signal. In addition, the weighted avg and stacking produced the same RMSE scores (0.6344), although other scores are different. This might suggest that the linear ridge basically learned weights approximately $[0.3, 0.7]$, so stacking approximately a weighted average. This often happens with only 2 models. To explore this, future work shall explore more models for the ensemble.

4.4 Hybrid RoBERTa on Track-B

Table 5 shows the performance of Hybrid RoBERTa on Track-B English data - Environmental Protection. The best hybrid configuration and the evaluation metrics are listed. Once again, the hybrid model performed the best over individual regression and bin-expected models.

5 Model Submissions

Due to unforeseen situations, we were only available to submit the system output for TaskA.1 using the Hybrid RoBERTa model, i.e., without the LLMs and ensemble-learning variations. In addition, we did not submit for Track-B. The initial/unofficial ranking from the organisers on our Hybrid ReBERTa (lightweight) shows that it achieved 16/30 and 22/33 on laptop and restaurant data, respectively. On laptop data, the best performing team has a score of 1,2408, while Hybrid RoBERTa has **1,4062**, which is closer to the best team and much better than the bottom-ranking team 1,8486 and baseline 2,8053. Similarly, on restaurant data, the best performing team has 1,1035 error score, while Hybrid RoBERTa produced **1,3632**, much better than the last team 1,9115 and baseline 2,791. Considering the very **low cost** from encoder-based Hybrid RoBERTa with **constrained** training, this performance is very promising, as shown in Table 8 and 9 for full ranking, and Table 7 for brief summary.

6 Conclusions and Future Work

In this system paper, we introduced a hybrid encoder model RoBERTa averaging the weighted performance of regression and discretized classification heads. In addition, we explored the prediction-level fusion (late fusion or model stacking) for ensembling the output scores of the hybrid encoder and LLM; however, for future work, we would like to explore different kinds of ensemble methods, e.g., stacking ensemble from (Romero et al., 2025), automatic hyper-parameter finetuning (Akiba et al., 2019), as well as multi-modal sentiment tasks (Lindevelt et al., 2026).

Limitations

There are some limitations from our work. 1) Due to time limitations, we did not apply LLMs and ensembles on the test set, but on the Dev set. We will explore our system performance on test sets offline.

Table 3: **Hybrid** RoBERTa results on the **Restaurant** development set for SemEval Task 1 (Valence/Arousal). The model combines a regression head and a hard-bin classification head; the *average* prediction is a weighted combination with `pred_weight = 0.5`. Best configuration and detailed dev metrics are shown.

Domain	Variant	MSE↓	RMSE↓	RMSE _v ↓	RMSE _a ↓	ρ_v ↑	ρ_a ↑	ρ_{mean} ↑
Restaurant	Regression	0.8176	0.9042	0.8212	0.9802	0.9205	0.6458	0.7832
	Bin-expected	0.5369	0.7327	0.8154	0.6395	0.9130	0.6408	0.7769
	Average ($w = 0.5$)	0.4919	0.7013	0.6692	0.7320	0.9217	0.6679	0.7948

Best config (Restaurant): `num_bins = 11`, `alpha_cls = 0.2`, `pred_weight = 0.5`.

Table 4: **Ensemble** results on the Laptop Dev set for SemEval Task 1 (Valence/Arousal). We compare simple averaging, weighted averaging, and ridge-regression stacking (out-of-fold, OOF) with and without additional VADER-based features. Best (lowest) RMSE among valid (non-leaking) settings is highlighted.

Setting	Method	MSE↓	RMSE↓	RMSE _v ↓	RMSE _a ↓	ρ_v ↑	ρ_a ↑	ρ_{mean} ↑
Without VADER	Avg	0.4095	0.6399	0.5835	0.6918	0.9391	0.6105	0.7748
	Weighted ($w=[0.3,0.7]$)	0.4025	0.6344	0.5629	0.6987	0.9421	0.6124	0.7773
	Stacking (Ridge, OOF)	0.4025	0.6344	0.5713	0.6918	0.9397	0.5893	0.7645
With VADER	Avg	0.4095	0.6399	0.5835	0.6918	0.9391	0.6105	0.7748
	Weighted ($w=[0.3,0.7]$)	0.4025	0.6344	0.5629	0.6987	0.9421	0.6124	0.7773
	Stacking (Ridge, OOF)	0.4079	0.6387	0.5718	0.6992	0.9396	0.5793	0.7594

Table 5: Track B (English) Environmental Protection — best hybrid configuration and DEV results.

	Best config	num_bins	α_{cls}	pred_weight (w)			
		21	1.0	0.3			
Variant	MSE	RMSE	RMSE _v	RMSE _a	Pearson _v	Pearson _a	
Regression	2.0287	1.4243	1.7162	1.0546	0.5311	0.2221	
Bin-Expected	2.2221	1.4907	1.8301	1.0464	0.5272	0.0664	
Average ($w=0.3$)	1.9661	1.4022	1.6932	1.0322	0.5312	0.2234	

Note. Pearson mean: Regression = 0.3766, Bin-Expected = 0.2968, Average = 0.3773. Also: $RMSE_{avg} = 1.4022$, $RMSE_{reg} = 1.4243$, $RMSE_{cls} = 1.4907$.

†Full-fit stacking is trained on the full dev set and evaluated on the same dev set; it is therefore optimistic and should not be used for fair model selection. OOF stacking is the appropriate estimate.

Model	MSE	RMSE	RMSE _v	RMSE _a	ρ
LLM (ICL)	0.484	0.695	0.633	0.752	0.757

Table 6: LLM dev results (Laptop).

Dataset	Rank	RMSE	Baseline
Laptop	16 / 29	1.4062	2.8053
Restaurant	22 / 32	1.3632	2.7910

Table 7: Summary of our system performance on the SemEval-2026 Track A.1 datasets. Lower RMSE is better.

2) To test model generalisability, we plan to explore the performance on languages other than English, such as Chinese. 3) For LLM Model selection, we applied larger models Gemini, Claude, and GPT. It would be more inclusive to include smaller LLMs for comparisons.

Acknowledgments

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Score ↓	Team	Rank
1,2408	LogSigma	1
1,2425	TeleAI	2
1,2769	Bert Kittens	3
1,2833	RPI Team	4
1,2942	SokraTUM	5
1,3048	NLANGPROC	6
1,3098	ICT-NLP	7
1,3261	PICT	8
1,3283	The Classics	9
1,3455	YangS_team	10
1,3501	NTNU-SMIL	11
1,3612	PALI	12
1,3654	Habib university	13
1,3841	Cortexa	14
1,3946	SCU_Mesclab	15
1,4062	QuadAI	16
1,4109	HUS@NLP-VNU	17
1,4190	Pixel Phantoms	18
1,4242	SCUZANE	19
1,4336	UNF-BMI	20
1,4394	PAI	21
1,4401	AILS-NTUA	22
1,4557	LexiCore	23
1,4562	NCL-BU	24
1,5073	EmberAI	25
1,5080	REGLAT	26
1,5412	hdharpure	27
1,5924	DUTH	28
1,8486	surface3	29
2,8053	Baseline	–

Table 8: Initial SemEval-2026 Track A.1 ranking on the English Laptop dataset. Lower scores are better. Our system, **QuadAI**, ranked 16th among participating teams and outperformed the official baseline.

A QuadAI Ranking Among Teams

We list the initial/un-official ranking we received for reference in Table 8 and 9 for full ranking on Track-A1 laptop and restaurant data respectively (Yu et al., 2026).

Score ↓	Team	Rank
1,1035	LogSigma	1
1,1812	Bert Kittens	2
1,1958	PICT	3
1,2006	RPI Team	4
1,2116	NLANGPROC	5
1,2139	TeleAI	6
1,2141	PAI	7
1,2270	SRCB	8
1,2277	SCU_Mesclab	9
1,2324	The Classics	10
1,2676	ICT-NLP	11
1,2745	HUS@NLP-VNU	12
1,2772	YangS_team	13
1,2846	NTNU-SMIL	14
1,2866	PALI	15
1,2990	NTNU-SMIL	16
1,3011	SokraTUM	17
1,3049	Habib university	18
1,3168	Scmh15	19
1,3270	Cortexa	20
1,3483	SCUZANE	21
1,3632	QuadAI	22
1,3656	Pixel Phantoms	23
1,3742	LexiCore	24
1,3920	UNF-BMI	25
1,3933	AILS-NTUA	26
1,4265	TeamLasse	27
1,4268	satyam_1909	28
1,4678	EmberAI	29
1,4861	NCL-BU	30
1,5003	hdharpure	31
1,9115	surface3	32
2,7910	Baseline	33

Table 9: Initial SemEval-2026 Track A.1 ranking on the English Restaurant dataset. Lower scores are better. Our system, **QuadAI**, ranked 22nd and outperformed the official baseline.